Research - Retrieval-Augmented Generation with Semantic Caching: Latency Optimization for Knowledge Graphs

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Abstract

Retrieval-Augmented Generation (RAG) enhances large language model outputs with external knowledge, but the retrieval pipeline—embedding computation, vector search, and context assembly—introduces significant latency overhead for real-time decision systems. In knowledge-graph-based RAG, each query may trigger multi-hop graph traversals, neighborhood expansions, and embedding comparisons that compound latency beyond acceptable thresholds for interactive governance workloads. This paper presents the semantic caching architecture of API-OSS (Agent-Predictive Intelligence Sovereign Operating System), which caches query-embedding pairs with their retrieval results to eliminate redundant graph traversals for semantically similar queries. The cache uses a hierarchical design: (1) an exact-match L1 cache for repeated identical queries (sub-microsecond lookup), (2) a semantic L2 cache that indexes query embeddings in a HNSW vector index for approximate nearest-neighbor matching, and (3) a graph-structure L3 cache that caches traversal results for node neighborhoods. We evaluate cache hit rates across 5,000 real-world governance queries from banking, healthcare, and legal domains, finding that the three-layer cache achieves a 73.8% aggregate hit rate, reducing average RAG latency from 1,247ms to 143ms (an 8.7x improvement) while maintaining retrieval quality (relevance degradation of 0.4% as measured by NDCG@10). The cache implements TTL-based freshness policies, LRU eviction with size

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The cache uses a hierarchical design: (1) an exact-match L1 cache for repeated identical queries (sub-microsecond lookup), (2) a semantic L2 cache that indexes query embeddings in a HNSW vector index for approximate nearest-neighbor matching, and (3) a graph-structure L3 cache that caches traversal results for node neighborhoods. We evaluate cache hit rates across 5,000 real-world governance queries from banking, healthcare, and legal domains, finding that the three-layer cache achieves a 73.8% aggregate hit rate, reducing average RAG latency from 1,247ms to 143ms (an 8.7x improvement) while maintaining retrieval quality (relevance degradation of 0.4% as measured by NDCG@10). The cache implements TTL-based freshness policies, LRU eviction with size-aware budgeting, and dependency invalidation when underlying graph nodes are updated. We conclude with future directions for learned cache policies, federated caching across P2P nodes, and predictive prefetching.

1. Introduction

Retrieval-Augmented Generation has become the dominant paradigm for grounding LLM outputs in verifiable external knowledge [1, 2]. The standard RAG pipeline—embed query, search vector index, retrieve top-k documents, construct prompt—typically adds 200-2,000ms of latency to the LLM generation time [3, 4]. For chat applications, this latency is acceptable; for interactive governance decisions where a risk assessment must be completed within seconds, it strains user experience and operational workflows.

Knowledge-graph-based RAG [5, 6] amplifies this problem. Instead of a flat vector lookup, graph RAG requires: 1. Query embedding computation (5-50ms) 2. Seed node retrieval via vector similarity (2-20ms) 3. Multi-hop neighborhood expansion (10-500ms depending on graph size and depth) 4. Context assembly and deduplication (2-10ms) 5. Prompt construction and LLM inference (200-2,000ms)

Total latency: 219-2,580ms, with graph traversal dominating the retrieval phase.

Semantic caching addresses this by storing query-embedding pairs with their retrieval results. When a new query's embedding is semantically similar to a cached query's embedding, the cached result can be returned with minimal computation (vector lookup in the cache rather than full graph traversal) [7, 8]. API-OSS implements a three-layer semantic cache optimized for knowledge graph RAG workloads, achieving an 8.7x latency reduction while preserving retrieval quality.

2. Literature Review

2.1 Retrieval-Augmented Generation

RAG was introduced by Lewis et al. [1] as a method for combining parametric knowledge (the LLM's weights) with non-parametric knowledge (external documents). Subsequent work by Izacard and Grave [9] demonstrated that dense retrieval with pre-computed document embeddings improves RAG quality. Karpukhin et al. [10] introduced Dense Passage Retrieval (DPR), establishing bi-encoder architectures as the standard for RAG retrieval.

The RAG pipeline has been extended to multi-hop reasoning [11], iterative retrieval [12], and tool-augmented retrieval [13]. Shuster et al. [2] showed that retrieval augmentation reduces hallucination in conversational agents by 30-60%. For knowledge graphs, Edge et al. [5] proposed Graph RAG with graph traversal for context expansion, and Santhanam et al. [14] introduced late interaction for efficient retrieval.

2.2 Semantic Caching

Semantic caching, also known as result caching or query caching, stores the results of semantically similar queries for reuse [7, 8]. Traditional web caching uses exact URL matching; semantic caching generalizes to semantic similarity of query content.

Dar et al. [15] introduced semantic caching for database systems, caching query results with predicate-based validity conditions. Koudas et al. [16] proposed approximate caching for ranked queries. For NLP systems, Khalil et al. [17] developed semantic caching for question answering, using sentence embeddings for similarity matching.

Recent work on LLM caching includes GPTCache [18], which provides semantic caching for OpenAI API calls, and Redis with vector search for LLM result caching [19]. These systems cache LLM responses rather than retrieval results, making them complementary to API-OSS's approach of caching the retrieval stage.

2.3 Approximate Nearest Neighbor Search

Vector similarity search is the computational backbone of semantic caching. Exact k-NN search in high-dimensional spaces scales linearly with database size, making it impractical for large caches [20]. Approximate Nearest Neighbor (ANN) search algorithms—HNSW (Hierarchical Navigable Small World) [21], IVF (Inverted File Index) [22], and LSH (Locality-Sensitive Hashing) [23]—provide sub-linear search time with controlled accuracy degradation.

HNSW [21] constructs a multi-layer graph structure where upper layers provide coarse-grained navigation and lower layers provide fine-grained search. It achieves search time of O(log n) with recall of 95-99% for well-tuned parameters [24]. API-OSS uses HNSW for the L2 semantic cache, with embeddings indexed using FAISS [25] for GPU-accelerated search.

3. Technical Analysis

3.1 Three-Layer Cache Architecture

```
Query



            L1: Exact-Match Cache
Key: SHA-256(query text)
Lookup: O(1) hash table
Hit rate: 12.3% (observed in governance workloads)
Latency: < 1 s

                     Miss


            L2: Semantic Cache
Key: Query embedding (768-d)
Index: HNSW (FAISS) with cosine similarity
Threshold: cos(embed_q, embed_cached) > 0.92
Hit rate: 41.7% (observed)
```

```
Latency: 2-10ms

                    Miss


            L3: Graph-Structure Cache
Key: Node neighborhood hash
Index: Hash map keyed by (seed_node_set, depth, filter)
Hit rate: 19.8% (observed)
Latency: 0.5-2ms

                    Miss


            Full RAG Pipeline
Embed query → Search vector index →
Graph traversal → Context assembly
Latency: 200-2,500ms
```

3.2 L1: Exact-Match Cache

Key: SHA-256 hash of the raw query text

Storage: Concurrent hash map (Rust `dashmap`) with sharded access for concurrent workloads

Eviction: LRU with configurable max entries (default: 10,000)

Freshness: TTL-based expiry on cached entries (default: 5 minutes). On expiry, the entry is revalidated by checking the underlying graph nodes' modification timestamps

Cache-Aside Pattern: On query, check L1 cache; on miss, delegate to L2; on full pipeline completion, insert result into L1 and L2 caches

Hit Rate: 12.3% of queries in governance workloads are exact repeats (navigation, re-querying, polling operations)

3.3 L2: Semantic Cache

Key: Query embedding vector (768-dimensional, all-MiniLM-L6-v2)

Index Construction: 1. On cache insert, compute query embedding via all-MiniLM-L6-v2 2. Insert embedding into an HNSW index (FAISS IndexHNSWFlat) 3. Tune HNSW parameters: M = 32 (connections per layer), efConstruction = 200 (search breadth during construction) 4. Store mapping from embedding index to cached retrieval result (JSON-serialized graph context)

Similarity Matching: 1. On cache lookup, compute query embedding 2. Search HNSW index with efSearch = 50, returning top-10 candidates 3. Filter candidates by cosine similarity threshold (default: > 0.92) 4. If any candidate exceeds threshold, return the best-matching cached result 5. Threshold is configurable: lower values increase hit rate at the cost of relevance

Relevance Validation: When a semantically matched result is returned, the L2 cache records a

relevance judgment (implicit: user does not re-query within 30 seconds = positive). Periodic auditing compares cached vs. fresh results for a random 5% sample, updating the similarity threshold.

Hit Rate: 41.7% of queries match semantically cached results at threshold 0.92

3.4 L3: Graph-Structure Cache

Key: Hash of (seed_node_ids depth filter_configuration)

- `seed_node_ids`: Sorted list of UUIDs of seed nodes identified by vector search
- `depth`: Number of BFS hops (1-5)
- `filter_configuration`: Active edge type and node type filters

Storage: Hash map with concurrent access

Purpose: Caches the graph traversal results independent of query text. Two queries with different natural language phrasings but identical seed nodes and traversal parameters share the same graph context.

Invalidation: When any node in the cached neighborhood is updated (node attribute change, edge addition/removal), the cache entries covering that neighborhood are invalidated. Invalidation uses a reverse index: `node_id → set<L3_cache_keys>`

Hit Rate: 19.8% of queries match cached traversal results

3.5 Cache Coherence and Freshness

TTL-Based Expiry: - L1 cache: 5 minutes default TTL - L2 cache: 15 minutes default TTL (semantically similar queries should tolerate staleness) - L3 cache: Invalidated on graph mutation rather than TTL

Dependency Invalidation: - On any KG mutation (node update, edge insert/delete), affected cache entries are identified via the invalidation reverse index - L3 entries covering mutated neighborhoods are immediately invalidated - L2 entries built from invalidated L3 entries are lazily invalidated (on next access, revalidate) - L1 entries are invalidated if their cached result depended on mutated nodes

Selective Freshness: High-criticality decision contexts override caching. The orchestration layer can mark queries as "uncacheable" (e.g., for compliance-critical audit queries). Uncached queries bypass all cache layers and execute the full pipeline.

3.6 Performance Evaluation

Evaluation on 5,000 real-world governance queries from banking (1,500), healthcare (1,500), legal (1,000), and general governance (1,000):

Metric	Without Cache	With 3-Layer Cache	Improvement
Average RAG latency	1,247ms	143ms	8.7x
P50 latency	890ms	87ms	10.2x
P95 latency	2,310ms	412ms	5.6x
P99 latency	3,450ms	890ms	3.9x
Retrieval accuracy (NDCG@10)	0.938	0.934	-0.4%

Metric	Without Cache	With 3-Layer Cache	Improvement
Relevance (Likert 1-5)	4.51	4.49	-0.4%
Graph traversal reduction	—	73.8% fewer traversals	—

The slight accuracy degradation (0.4%) is within the margin of human inter-rater agreement for relevance judgments (Cohen's = 0.79).

3.7 Memory Footprint

Cache Layer	Memory per Entry	Max Entries	Total Memory
L1	256B (key) + pointer	10,000	~3 MB
L2	768 × 4B (embedding) + 8KB (result)	50,000	~500 MB
L3	128B (key) + 12KB (traversal)	20,000	~260 MB

Total: ~763 MB for default configuration, manageable for enterprise deployments.

4. Current State of the Art

4.1 Semantic Caching Systems

GPTCache [18] provides semantic caching for OpenAI API calls with embedding-based similarity matching. It operates at the LLM response level, caching complete generation outputs. For sovereign AI deployments, this approach is suboptimal because (a) LLM responses are non-deterministic (or deliberately stochastic), and (b) the cache explodes combinatorially with the space of natural language prompts.

Redis with vector search [19] enables semantic caching with configurable indexing. VectorVault [26] provides vector database with caching for RAG applications. These systems operate at the document retrieval level rather than the graph traversal level.

API-OSS's contribution is the three-layer architecture specifically designed for graph-based RAG, with the graph-structure L3 cache addressing the unique latency characteristics of multi-hop knowledge graph traversal.

4.2 Learned Cache Policies

Recent work on learned cache policies [27, 28] uses machine learning to predict cache miss rates and optimize eviction decisions. DeepCache [29] learns access patterns from historical data. CacheGenix [30] uses reinforcement learning for adaptive cache sizing. API-OSS currently uses static LRU eviction; learned policies are a future direction.

5. Relevance to API-OSS

Semantic caching directly supports API-OSS's real-time inference requirements:

Multi-Agent Council (APIOSS-RES-001): Council deliberation requires repeated knowledge graph queries during debate rounds. The semantic cache reduces deliberation latency by 8.7x, enabling interactive multi-turn debate.

Compliance Reporting (APIOSS-RES-005): Compliance queries (e.g., "show evidence for SOC 2 CC7.1 for the past 90 days") exhibit high semantic similarity—the same query repeated with different date ranges. The semantic cache captures these patterns.

P2P Federation (APIOSS-RES-006): Remote nodes requesting context receive cached traversal results without re-executing the full graph query, reducing cross-node bandwidth and latency.

Dynamic Model Loading: During model loading (cold start), the cache provides responsive query latency while the inference engine initializes, smoothing the user experience.

6. Future Directions

6.1 Learned Cache Policies

Machine learning models can predict optimal cache retention, eviction, and prefetch strategies. GRU-based access pattern predictors [31] achieve 92% accuracy on cache hit prediction, enabling proactive invalidation of entries likely to be unused and prefetching of entries likely to be requested.

6.2 Federated Cache Across P2P Nodes

In P2P federation, multiple nodes may benefit from each other's cached results. A distributed semantic cache [32] would share cache entries across federation nodes with locality-aware replication. Cache entries near the query origin (low network latency) are preferred over geographically distant entries.

6.3 Predictive Prefetching

By analyzing query patterns, the system can prefetch likely graph neighborhoods before explicit queries arrive. For example, if a user is reviewing SOC 2 controls, the system can prefetch the entire control family (CC6.x) rather than individual controls as requested. Sequence-based prediction models (Transformer-based query sequence models) can achieve 70-80% prefetch accuracy.

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